Are Personalized Recommendations the Savior for Online Content Providers?

Philipp Bodenbenner
Dirk Neumann

Veröffentlicht in:
Multikonferenz Wirtschaftsinformatik 2012
Tagungsband der MKWI 2012
Hrsg.: Dirk Christian Mattfeld; Susanne Robra-Bissantz

Braunschweig: Institut für Wirtschaftsinformatik, 2012

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Philipp Bodenbenner

Albert-Ludwigs-Universität Freiburg, Institut für Wirtschaftsinformatik, 79085 Freiburg,
E-Mail: philipp.bodenbenner@is.uni-freiburg.de

Dirk Neumann

Albert-Ludwigs-Universität Freiburg, Institut für Wirtschaftsinformatik, 79085 Freiburg,
E-Mail: dirk.neumann@is.uni-freiburg.de

Abstract

Advertising seems to be the major stream for generating revenue with online content. Therefore, it is crucial for online content providers to create heavy traffic on their pages. Recommender systems have already been evaluated on their positive impact in e-commerce settings. In our evaluation we show that personalized recommendation as well change the user behavior and improve the relevant economic KPIs for content providers. To show these effects we put up a model that inter-relates all components of an advertising-based revenue stream. We formulate a set of hypotheses on those components, which can be influenced by recommender systems: exposure and stickiness, indicating customer engagement, as well as the content portfolio that impairs the appealed user base. The hypotheses are tested in a study that is being conducted based on a real-world data set from a German newspaper.

1 Introduction

The Internet features millions of content-based web pages that provide a vast array of information. Content includes news articles, directories, forums, blogs and other information. In contrast to e-commerce web pages (online shops, etc.), content providers face the challenge of establishing a viable business model. Much research has already been done on developing business models for the content & media industry in the Internet. One example is the categorization of revenue models for online content proposed by Mings and White [30]: subscription, advertising, transactional, and bundled. The highest level strategic decision for online content providers is to decide whether to offer their content for free or for a fee. Some firms offer parts of their content for free, and charge for other content (e.g. archive). Again and again online content providers try to substitute advertising with a revenue stream based on subscriptions. One prominent example that has failed is the New York Times. Their paywall was removed again shortly after setting it up by reason of a low growth in subscription base, compared to the growth in online advertising. Literature reveals further confirmation of this assumption. For example, the total revenue of newspapers splits up as follows: 81.5% are being earned with advertising; the restis based on subscription [13]. Advertising is being perceived as the primary and dominant source for revenue for the vast majority of online content providers ([20], [40]). This revenue structure is also being expected to coin the future online content market [39]. Altogether, business models with revenue streams that are based on subscription fees have become less attractive and viable [26], as users want to get access to online information free of charge. Thus, generating revenue with advertising-based models seems - at the moment - to be the only way that works. We focus our evaluation to the latter kind of revenue models in the space of online content providers. Since advertising is dominating the content providers' revenue streams, it is crucial for them to create heavy traffic on their pages and keep the readers to their pages as long as possible. Accordingly, it is important to create a loyal base of frequently recurring customers and to increase the length of each visit to the page. Online news reading has become very popular as the web provides access to news articles from millions of sources around the world. Today, content-based web pages offer several thousand articles to their users. Out of these, only a few articles can be featured (for a limit period of time) on landing pages. Thus, it is a key challenge of content pages to help users find the articles that are interesting to them to read. The large article databases demand new techniques for prioritizing and presenting items of potential interest quickly and easily to users. Thereby, challenges arising from data's size and heterogeneity as well as from dynamics of user interactions need to be addressed [22]. Thus, efficient tools are required to decrease search costs and foster personalized information delivery. To create an effective personalization, all available data reflecting the user behavior has to be taken into account. Recommender systems particularly serve these requirements. They allow accomplishing personalized information delivery on the basis of numerous data sources. In the process, they focus on user-dependent filtering and selection of relevant pieces of information [22]. Recommender systems are a rather new field of academic research, becoming a focus of interest in the mid-1990s (e.g.[34], [35]). Three major groups of recommender systems can be distinguished, namely content-based, collaborative filtering and hybrid approaches [1].Content-based recommendations create their filtering based on a similarity measure between the items, i.e. items having similar attributes are supposed to be closely related. On the contrary, collaborative recommendations provide users with items that were visited by people with similar preferences in the past. Hybrid approaches build recommendations based on a combination of both content-based and collaborative methods. By now, algorithms based on collaborative filtering are the most popular among online retailers for recommendation of products [32].In the beginning, system design as well as the technical efficiency and predictive accuracy have been the primarily focus of evaluation of recommender systems (e.g. [23], [36]). Understanding the behavioral effects on users and impact on key economic performance indicators has only been subject of research recently. Examples for such evaluation are two studies conducted on the basis of real-world data from Amazon.com [28] and LeShop, a Swiss grocery store [17]. These studies analyzed the business value of personalized recommendations including the direct and indirect impact on revenue. A study by Pathak et al. [32] analyzed the impact on sales and price of individual items recommended by the system and revealed different ways of influencing the visitors. First, the uncertainty of quality of the recommended items is reduced. Second, signaling and advertisement effects induced by the recommendations exhibit cross-selling opportunities. Third, recommender systems can help build customer loyalty and increase switching costs. The largest group of studies focuses on analyzing the effects on sales diversity or concentration patterns ([8],[9],[21][41]). Hinz and Eckert[24] compare multiple search systems (i.e. hit list, recommender systems, etc.) and additional consumption respectively substitution effects. Their research shows that recommenders lead to substitution, which can be beneficial for retailers when niches yield higher margins than substituted top-sellers. Online recommendations can even be more influential than human ones [37].As shown, most studies that have hitherto been conducted have dealt with the impact of recommender systems on sales in e-commerce settings. Corresponding effects on content-based services have only marginally been evaluated so far. We address this research gap and try to find answers to the overarching question: do recommender systems entail an impact on the user behavior in a content page setting, and improve the relevant economic performance indicators in advertising-based revenue models? To show these effects we put up a model that inter-relates all components of an online content provider's revenue stream. We formulate a set of hypotheses on concepts, which can be influenced by recommender systems, and test them in a study. The study is being conducted based on a substantial real-world data set from a major German newspaper. Core of the study is two-group experiment comparing usage data from a test group with a control group. The control group was provided with random links instead of real, personalized recommendations. The paper is structured as follows: First, we describe our research framework and the related hypotheses. Subsequently, the study environment is presented. Finally, the hypotheses are evaluated in the study environment and results are derived.

2 Research Framework

For our research framework we have to extract the nucleus of revenue streams of content-based websites. The basis for this is a group of performance indicators–so-called web metrics–that have been defined within the realm of web analytics. The topic of web analytics (synonym: web controlling) is rather new and scientifically still in its infancy. Recently, a few reference books dealing with web analytics have been published (e.g.[33]). In addition, a standardization body, the Web Analytics Association, has published a compendium that provides definitions for most web metrics [11]. According to Bhat et al. exposure or popularity of a web page, as well as stickiness are core objectives of web pages [5]. These concepts reflect customer engagement, which is a key driver for an effective online customer relationship and accordingly successful online content services. In addition, these two concepts are supplemented by a third concept content portfolio that characterizes the depth of usage of a providers' content base. Together with the external factor "profit" these concepts determine the final outcome, which is total revenue of the content provider.

Concept: Exposure. The first objective, exposure, reflects the number of total visits a web page exhibits. This embraces both the number of unique visitors as well as their average number of visits to the web page[5].The key figure "number of unique visitors" resembles the sum of users that frequent a web page within a certain time frame [11]. For web pages that rely on advertising revenue models, having a large number of visitors is crucial. New visitors have to be acquired and should view as many different pages and pieces of content as possible in order to generate advertising views. The second factor of the exposure cluster is the average number of visits per visitor (synonym: loyalty). This shows visitor retention and measures the number of times a visitor has shown up on the web page within a given period.

Concept: Stickiness. The second objective is stickiness, which measures the overall visit duration on a web page [16]. Moreover, stickiness indirectly measures the relevance of provided information and the associated satisfaction of users as well and is derived from the number of page views per visit and the average time spent per page. A visit (synonym: user session) denotes usage sequences that are associated with regards to content and time, and that can be related to a certain user [33]. Inactivity between two user activities exceeding a certain threshold implies the end of the old visit and the start of a new visit. 30 minutes have proven as de-facto standard for the inactivity threshold [6].The most prevalent measure for comparison of web pages is the number of page views, also known as page impression. Moreover, it indicates the strength of connection between the visitor and the information provided on the web page [33]. The number of page views is an excellent indicator of how compelling and easy to navigate visitors find a web page. For content-based web pages, a measure of success is getting visitors to look at a large number of pages. The larger this number, the greater number of pages viewed in an “average” visit. Furthermore, stickiness is determined by the average time spent per page. This describes the timespan between entering and leaving a single web page [33]. This metric helps to measure the overall goal of increasing the amount of time users spend on a web page during a given visit. Multiplied with the average page views per visit, it results in the average time spent on the web page. The duration of a web page visit is important since there is still value derived from mere exposure to advertisements [7].

Concept: Content Portfolio. With the expansion of online channels and the fact that online stores are able to display a much larger number of products than regular stores, consumption moves away from being concentrated on a small number of popular items only (e.g. [18], [42]). With the help of online search and filtering tools, customers can also search for and discover the lower-selling niche products off the list of top sellers, the so-called "long tail" [2].The long-tail phenomenon is particularly relevant for information goods and online content (e.g. news, music) that can be digitized and distributed at virtually no cost via the Internet[4]. Due to the fact that production and distribution costs for these goods approach zero, the tail can be extremely long, outplaying the traditional 80/20 Pareto principle of offline channels ([9], [19]). This makes the strategy of extending a top seller portfolio by a sub-stantial long tail promising for online content providers. A long tail portfolio has an increased relevance for a broader audience, since it addresses both mainstream and niche interests. Therefore, it positively affects users’ loyalty (exposure) and their visit duration (stickiness).

External Factor: Profit. As described beforehand, most content-based web pages rely on advertising as revenue stream. For online advertising there exist two major classes of pricing models, namely “Cost-per-Mille” (CPM) and “Cost-per-Click” (CPC) pricing [20]. CPM-based pricing is based on the total number of page views of a web page. Advertisers pay for exposure of their banners to a specific audience that is measured per thousand impressions. The problem with CPM advertising is that advertisers are charged even if the target audience does not click on the advertisement. Cost-per-click advertising, the second type of pricing model, overcomes this problem by charging advertisers only when the consumer clicks on the advertisement. So, not only are pure page views important, but also the time a user spends on each page. This is due to the fact that an increased page exposure time concurrently increases the probability that a user clicks on an advertising banner. This phenomenon has been evidenced in different studies (e.g. [10]).

Outcome: Total Revenue. The analysis of online customer behavior aims at maximizing the revenue and profitability of the e-business, be it an e-commerce or content-based web page [43]. Based on the previously described performance indicators, the overall revenue of a web page that is based on advertising can be calculated. The resulting revenue is derived from multiplying exposure and stickiness with the profit component.

The five previously described components (i.e. concepts, external factor, and outcome) together form our research framework. This framework creates a relation between the metrics that are relevant to revenue generation of content-based web pages (see figure 1).

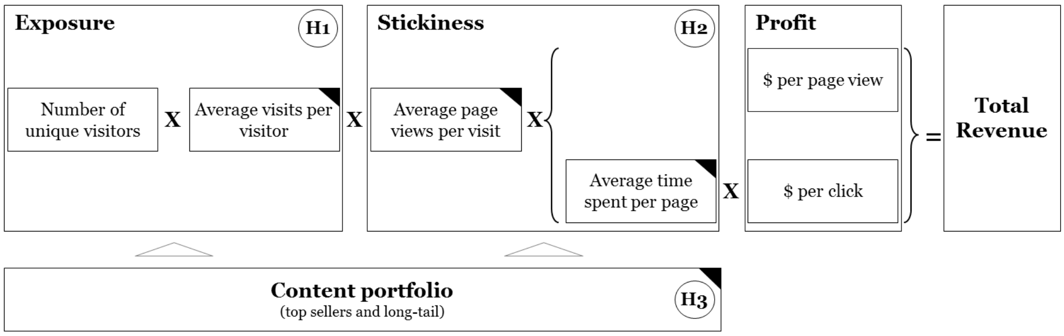

Figure 1: Aggregated Research Framework. Triangles indicate components on which an impact by recommendations is assumed. Hypotheses H1-H3 are formulated to verify that

Personalization has proven to be a key driver for building up user loyalty towards a web page (e.g. [3],[32]). There are several ways to achieve personalization, with recommender systems being a very promising. Recommender systems provide added value for the user, create a relationship with the user, and attract users to return to the site ([36]). The more a user visits a page the more a recommender system learns about his preferences and, consequently, the recommendations become more accurate. This in turn increases the loyalty again and increases switching costs ([32],[36]).In an experiment with Google News, the frequency of website visits significantly increased for the test group compared with the control group [29]. On average, the frequency of website visits in the test group was 14.1% higher than the control group. We consolidate these findings into the following statement:

Hypothesis 1:
Showing personalized recommendations amplifies exposure of content to customers, i.e. personalized recommendations increase average visits per visitor.

Our research found no sources relating to the impact of recommender systems on the stickiness of web pages. However, there is research that covers related resp. comparable metrics, such as search costs, loyalty, trust, and number of products sold (for e-commerce settings). These insights can be taken as baseline and valuable input for formulation of our second hypothesis. Recommender systems drive down search costs. Thus, they are only needed when search costs are high [12], which particularly applies to online content bases with thousands of accessible content pages. Items with high search costs can particularly profit: showing more recommendations significantly increases their sales figures. For easy-to-find items and small-sized content bases, recommendations could not achieve a major improvement. By decreasing search costs, recommender systems manage to guide users quicker and easier towards information they are looking for and thusly support overcoming the information overflow [15].

Moreover, personalization, which is the core of recommender systems, increases the relevance of shown links on a web page. Most users visit news websites with the attitude of “show me something interesting,” rather than having any specific information goals [14]. Efficient recommenders can help provide users with more relevant content and thus “stick” users to websites and motivate them to click on recommended links, since they fit users’ current preferences [15]. The perception of personalization significantly increases customers’ readiness to build up trust [27]. Trust is especially important in the information-based society, where attention is a scarce resource [15]. An experiment conducted with Google News showed that an enhanced personalization of news recommendations created a more focused reading in the test group [29]. Users seemed to pay more attention and spend more time in the recommended news section. Even when the total amount of attention users were willing to pay per visit stayed constant, they clicked on more recommended news articles. A similar coherence between recommender systems and stickiness is shown by another work [24]. This study analyzed the impact of recommender systems on the number of products that can be sold. In this e-commerce setting it could be observed that recommender systems lead to substitution and not additional consumption; different results were achieved when analyzing other search systems, such as hit lists. A more positive relation between recommender systems and business value can be seen in a study where personalized recommendations were delivered through a mobile internet platform [22]. The effective sales could be increased by up to 3.6 percent as compared with the existing non-personalized system. In summary, there seems to be coherence between the impact of recommender systems and stickiness of a web page. We propose that all in all, the attractiveness of a web page is being increased by recommender systems. This entices users to stay longer on the respective pages and perform more clicks. Thus, we raise the following hypothesis:

Hypothesis 2:
Showing personalized recommendations increases stickiness of a content page.

a. *Personalized recommendations positively impact the number of page views per visit.*

b. *Personalized recommendations lead to more intensely read content pages.*
Thus, the average time spent on a website is increased.

A focal point of present studies and research related to recommenders’ non-technical impact is on sales concentration respectively diversity. So far, the findings have been derived from e-commerce settings (i.e. online shops recommending products, and not content). Two oppositional trends can be found in literature. There is a small group of mainly older research that found evidence for increase in sales concentration when employing recommender systems (e.g. [31]). This means the popularity of already popular products, so-called blockbusters, is further reinforced. The long tail is focus of the second existing group of research. This much stronger and more recently-active group proves recommender systems help consumers discover new products and thus increase sales diversity ([8],[9],[21]). That means hitherto niche items are being recommended and adjacently read, respectively sold, more often. For example, a study evaluating sales behavior for cigars showed that recommendations stimulate users to buy cigars other than the well-known ones and thus increase sales diversity [41]. This is especially interesting from an up- and cross-selling perspective. We follow the impression of the latter group and deduct our third hypothesis:

Hypothesis 3:
Personalized recommendations lead to diversity in the visited content base - from recently top viewed content to the long tail: breadth of visited article base, the contents' age as well as the articles' category.

3 Study Design

Our examinations focus on one specific type of content-based web pages, namely online newspapers. Nonetheless, our findings can be easily translated to other content-based services. To evaluate our research framework we are able to conduct a study based on usage data from a major player in the German newspaper market. The site employs a YOOCHOOSE[1] recommender system to provide personalization to its visitors. The dataset for our study is derived from a two-group experiment that recorded usage data from a test group and a control group over a period of one week (24/7). The full dataset comprises of around300k records[2]. The groups are constituted randomly based on the last digit of the user's session identifier, and they are virtually equal in size (test group = 53,828 unique users, control group = 53,604). Any further characteristics about the groups are not known. During the testing period the test group was provided with "real" personalized recommendations, whereas the control group was shown arbitrary links[3]. We have to hazard the consequences of well-known constraints that arise from collecting anonymous measuring data without user login. For example, the refusal of session cookies, multiple persons using one device, and persons using multiple devices lead to inaccuracy in determining user sessions as well as the uniqueness of users. We assume that this effect is balanced out over the two groups and the large number of observations that we take into account.

4 Study Results

In the following, we present an excerpt of results that we derived from our study. For evaluation of data we have clustered the observations into different segments (see figure 2).

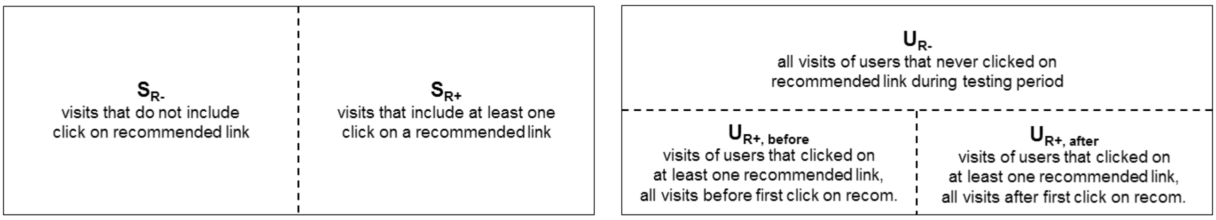

Figure 2: Segmentation of Study Observation Data

Hypothesis 1. The first hypothesis targets at the impact of personalization on the exposure component of a content website (i.e. average visits per user).Firstly, we evaluate the observed data within the test group, and compare users that never clicked on a recommended link with those that have reacted to such a link at least once (i.e. U_{R-} and U_{R+}).The Wilcoxon-Mann-

[1] YOOCHOOSE (www.yoochoose.com) employs a hybrid recommendation engine, combining both stereotype and collaborative filtering algorithms (Inbar et al. 2008).
[2] Three types of events are being recorded: click on link, click on recommended link, and article read.
[3] The personalized recommendations as well as the arbitrary links were shown at the same position and layout on the page.

Whitney test calculates a critical value z that lies outside the boundaries of the 97.5% confidence interval (see test 1). Hence, the null hypothesis (i.e. actual location shift between distributions of visits is greater than 0) can be rejected. Consequently, the average visits per user are stochastically higher for those users that have clicked on at least one recommendation during the testing period. Hypothesis 1 is accepted for this part. Secondly, we compare the observed values of the test group with the control group. Results of the Wilcoxon-Mann-Whitney test are inconclusive (see test 2). Thus, a significant advantage of the personalized recommendations, i.e. more visits per user, over the arbitrary links cannot be witnessed. Nonetheless, the observations show that personalized recommendations have a positive impact on "converting" users into members of cluster U_{R+}, which contains the more loyal users. The percentage of users that clicked at least one recommendation (U_{R+}) is more than 30% higher for the test group (4.7% of users) compared with the control group (3.5%). This again leads to a higher total average of visits per user. Unfortunately, this effect cannot be fully validated. For interpretation, the position of the recommendations on the web page needs to be taken into account. The recommended links are presented on the lower end of a content page. Thus, they are recognized by a small percentage of visitors only, which results in a limited influence of personalized recommendations on the full usage data set.

	1) Visits/user		2) Visits/user		3) Clicks/visit		4) Clicks/visit		5) Reads/visit		6) Reads/visit	
	U_{R-}(t)	U_{R+}(t)	U_{R+}(t)	U_{R+}(c)	U_{R-}(t)	U_{R+}(t)	$U_{R+,a}$(t)	$U_{R+,a}$(c)	S_{R-}(t)	S_{R+}(t)	$U_{R+,a}$(t)	$U_{R+,a}$(c)
$\bar{x}$	1.32	2.45	2.45	2.36	1.37	2.59	2.88	2.81	0.94	2.57	1.09	2.05
s	1.03	2.16	2.16	1.91	0.90	2.34	2.51	2.22	0.95	2.14	1.08	1.92
s^2	1.06	4.69	4.69	3.65	0.82	5.49	6.29	4.95	0.91	4.62	1.16	3.68
m / n	54,063	4,948	4,948	3,567	48,757	4,408	3,397	2,529	65,282	2,246	2,529	3,397
U	24,972,877		1,504,519		61,588,508		4,241,732		31,177,482		6,197,921	
interval	]-∞; -4.35e-05]		]-∞; 2.91e-05]		]-∞, -0.999999]		]-∞, 6.83-05]		]-∞, -1.000048]		[0.99996, ∞[	
z	-5.51e-06		-1.40e-05		-0.999994		-9.91e-07		-1.000047		0.99992	

Table 1: Overview on results from Wilcoxon-Mann-Whitney tests[4], α = 2.5% for all test runs

Hypothesis 2a. Hypothesis 2a sets the focus of attention to the stickiness of a content page: do personalized recommendations help to extend a single visit of a user (i.e. increase the average number of page views)? Again, we start by evaluating the observed data within the test group (U_{R-} vs. U_{R+}). The observed mean of average page views per visit is considerably higher for the cluster using personalized recommendations ($\bar{x}_{UR+} = 2.45$; $\bar{x}_{UR-} = 1.32$). A Wilcoxon-Mann-Whitney test confirms this assumption (see test 3); the null hypothesis can be rejected. Hence, personalized recommendations entail a significant increase in page views per visit. Hypothesis 2a is accepted for this part. Secondly, we analyze differences in the impact of using recommended links between the test and control group. Results of the Wilcoxon-Mann-Whitney test are inconclusive (see test 4). "Personalization", even when arbitrary links can be considered as placebo, has a considerable impact as such, but hypothesis 2a cannot be accepted when it comes to showing advantages of personalized recommendations over arbitrary links.

[4] A chi-quadrat-test showed that the observed values are not normally distributed. The Wilcoxon test can be applied since the observed values are ordinal and observations from therespectively compared groups are independent of each other.

Hypothesis 2b. When the user visits a page, a read event is triggered after a certain time. We use the number of these events to measure the average visit duration. For evaluation of hypothesis 2b we perform a Wilcoxon-Mann-Whitney test to compare the distributions of read events for visits with and without clicks on recommended links. The observed means of read events per visits show a clear tendency ($\bar{x}_{SR+}$ = 2.57; $\bar{x}_{SR-}$ = 0.94). The testing confirms this observation. The null hypothesis can be rejected, and hypothesis 2b is accepted for this part. The number of reads per visits is stochastically greater for visits that include clicks on recommendations. Next, we compare the test group's cluster $U_{R+,after}$ with the control group. Again we employ a Wilcoxon rank sum test, which results in rejection of the null hypothesis stating that the location shift between control group and test group is less than 0. This result is surprising at first sight: the average number of read events per visit is stochastically higher when showing arbitrary recommendation links, and not (as assumed) for personalized recommendations. This result is possibly biased by the way we measure the read events. When a user clicks on an arbitrary recommended link he is pushed into a setting that is (most probably) not linked to the prior page. The user requires a certain time to conceive the context and content of the newly called page. Since the read event is triggered after a certain time, the user is still in the state of getting familiar with the new context and not really reading yet. Read events that follow clicks on a personalized recommendation consequently exhibit a higher probability that the content has been really consumed.

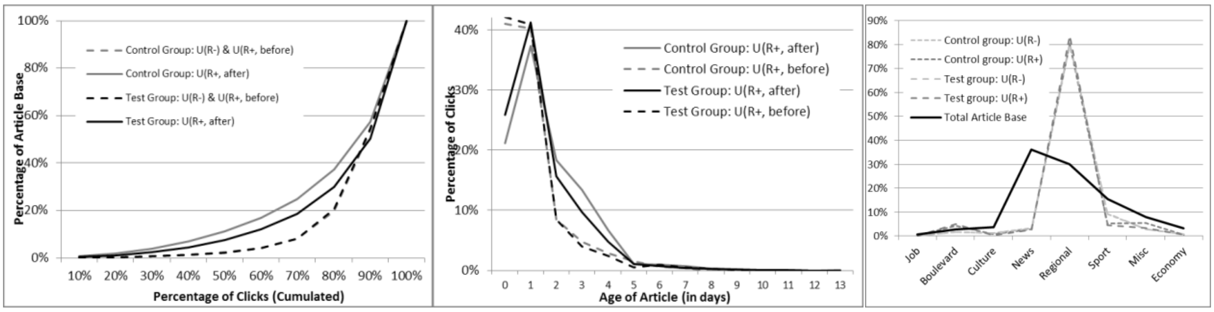

Figure 3: a) Clicks in relation to visited articles; b) … to age of articles; c) … to categories

Hypothesis 3. The diversity of visited content can be evaluated along different dimensions. Firstly, we evaluate the impact on the breadth of the visited article base. For all users that have not clicked on any recommended link, the breadth of the visited article base follows the Pareto principle (80/20), i.e. 80% of the clicks address 20% of the article base. This behavior changes when users start to use recommended links. As figure 3a shows the diversity of visited articles considerably increases. For personalized recommendations 80% of the clicks are distributed to 30% of the article base. The effect is even stronger for arbitrary links, where the ratio amends to 80/40. The differences between the effects of personalized recommendations and arbitrary links can be explained by the nature of the employed recommender engine. It proposes articles to the user that are "closer" to the original content. To further substantiate the results, we perform a chi-square-test (cross tab) to compare the percentage of viewed article base with the percentage of clicks (for test group: U_{R-}&$U_{R+,before}$vs. $U_{R+,after}$). The test value X^2 (76.88) exceeds the critical value (10.83) for a significance level of 99.9% (dimension factor = 1).Hence, the null hypothesis (i.e. coverage of article base is similarly distributed for both standard and recommended links) can be rejected. Novelty of the visited content is the second dimension that is assumed to be impacted by personalized recommendations. The impact of recommended links on the age of visited articles is being shown in figure 3b. Again the recommendations lead to a more widespread consumption of articles, i.e. articles that are older than one day are more frequently being accessed. On the contrary, very current articles (i.e. age < 1 day) are being less visited. As for the breadth of article base, the arbitrary links generate a broader spread. Thirdly, drawing the distribution of clicks over the articles' categories shows a surprising result (figure 3c): the distributions seem to be similar for all user clusters (across both the test and control group), and the considerably deviate from the distribution of the total article base. This can be explained by the way the newspaper's website is structured. Since the dataset is derived from a regional newspaper, regional news is very strongly featured on the landing page. Recommended links are not being shown on the landing page, but only on the actual news articles. Consequently, the user is already impaired with a certain content focus when being exposed to the first recommended link. Summing up, hypothesis 3 is accepted concerning the effects related to the breadth and novelty of the visited articles.

5 Managerial Implications and Conclusion

Content providers are searching for viable business models in the Internet. Currently, a revenue stream based on advertising seems to be most promising. Therefore, content providers need to attract their visitors with relevant and personalized content. As our study in an online newspaper setting demonstrates, recommender systems can contribute to this and significantly improve the revenue stream of a content provider. The study results suggest that recommender systems entail a positive influence on key business performance indicators of a content business model, namely exposure, stickiness and the content portfolio. The exposure is significantly improved by increasing the users' loyalty. Stickiness is amended as well: the length of stay both in terms of page views and time spent on the page are positively affected. Furthermore, personalized recommendations entail the consumption of a broader range of content both in dimension of varied articles and contents' novelty. In the near future, we plan to conduct further evaluations to compare effects of different recommender systems (e.g. popularity). Moreover, we want to extend our research to the actual content to evaluate whether recommendations within or across different categories entail diverse effects.

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